FACIAL EXPRESSION DETECTION USING PRINCIPAL COMPONENT ANALYSIS

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF

Master of Technology

In

TELEMATICS AND SIGNAL PROCESSING

By

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Department of Electronics and Communication Engineering

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Under the Guidance of

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NATIONAL INSTITUTE OF TECHNOLOGY
ROURKELA

CERTIFICATE

This is to certify that the thesis titled **"FACIAL EXPRESSION DETECTION USING PRINCIPAL COMPONENT ANALYSIS"** submitted by **Mr. MAHESH KUMAR VULLY**in partial fulfillment of the requirements for the award of Master of Technology degree in **Electronics & Communication Engineering** with specialization in "**Telematics and Signal Processing**" during session 20010-2011 at **National Institute Of Technology, Rourkela** (Deemed University) is an authentic work by him under my supervision and guidance.

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ABSTRACT

Face recognition has been very important issue in computer vision and pattern recognition over the last several decades. One difficulty in face recognition is how to handle the variations in the expression, pose and illumination when only a limited number of training samples are available. In this project Principal Component Analysis (PCA) is proposed for facial expression detection. Initially the eigenspace was created with eigenvalues and eigenvectors. From this space, the eigenfaces are constructed, and the most relevant eigenfaces have been selected using Principal Component Analysis (PCA). With these eigenfaces the input test images are classified based on Euclidian distance.

The proposed method was carried out by taking the picture database. The database was obtained with 10 photographs of each person at different expressions. These expressions can be classified into some discrete classes like happy, anger, disgust, sad and neutral. Absence of any expression is the “neutral” expression. There are 30 persons in database. The database is kept in the train folder which contains each person having all his/her photographs.

Another database was also prepared for testing phase by taking 5 photographs of 30 persons in different expressions and viewing angles but in similar conditions (such as lighting, background, distance from camera etc.). And these database images were stored in test folder.

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Chapter 1

1.1 INTRODUCTION:

Face is the primary focus of attention in social intercourse, playing a major role in conveying identity and emotion. Although the ability to infer intelligence or character from facial appearance is suspect, the human ability to recognize face is remarkable. We can recognize thousands of faces learnt throughout our lifetime and identify familiar faces at a glance even after years of seperation. This skill is quite robust, despite large changes in the visual stimulus due to viewing conditions, expression, aging and distractions such as glasses or changes in hair style or facial hair.[1]

Computational models of face-recognition, in particular, are intresting because they can contribute notonly to theoretical insights but also to practical applications. Computers that recognize faces could be applied to a wide variety of problems, including criminal identification, security systems, image and film processing, and human computer interaction. Unfortunately, developing a computational model of face recognition is quite difficult, because faces are complex, multidimensional and meaningful visual stimuli.

The user should focus his attention toward developing a sort of early, pre attentive pattern recognition capability that does not depend on having three-dimensional information or detailed geometry. He should develop a computational model of face recognition that is fast, reasonably simple, and accurate.

Eigenface is a face recognition approach that can locate and track a subject's head, and then recognize the person by comparing characeristics of the face to those of known individuals.

The computational approach taken in this system is motivated by both physiology and information theory, as well as by the practical requirements of near-real-time performance and accuracy. This apporach treats the face recognition problem as an intrinsically two-dimensional (2-D) recogniton problem rather than requiring recovery of three-dimensional geometry, taking advantage of the fact that faces are normally upright and thus may be described by a small set of 2-D characterstic views.

1.1.1 APPLICATIONS OF FACE-RECOGNITION

There is a large number of commercial, security, and forensic applications requiring the use of face-recognition technologies.

- These applications include automated crowd surveillance, access control, face reconstruction, design of human computer interface (HCI), multimedia communication, and content-based image database management.
- Photos of faces are widely used in mug shot identification (e.g., for passports and driver's licenses), where the possession authentication protocol is increased with a photo for manual inspection purposes; there is wide public acceptance for this biometric identifier.
- Face-recognition systems are tending to intrude from a biometric sampling point of view, requiring no contact, nor even the awareness of the subject.
- The biometric works, or at least works in theory, with old or no longer used photograph data-bases, videotape, or other image sources.
- Face-recognition can, at least in theory, be used for screening of unwanted individuals in a crowd, in real time.
- It is a fairly good biometric identifier for small-scale verification applications.

1.1.2 LIMITATIONS IN FACE-RECOGNITION

Even though current machine recognition systems have reached a certain level of maturity, their success is limited by the conditions imposed by many real applications. For example, recognition of face images acquired in an outdoor environment with changes in illumination and/or pose remains a largely unsolved problem. Ambient lighting changes greatly within and between days and among indoor and outdoor environments. Due to the 3D structure of the face, a direct lighting source can cast strong shadows that accentuate or diminish certain facial features. However, it is still a difficult task for a machine to recognize human faces accurately in real-time, especially under variable circumstances such as the 3D head pose, Illumination (including indoor / outdoor), Facial expression, occlusion due to other objects or accessories (e.g., sunglasses, scarf, etc.), Facial hair, aging. The similarity of human faces and the unpredictable variations are the greatest obstacles in face-recognition. [10]

The illumination problem is basically the variability of an object's appearance from one image to the next with slight changes in lighting conditions and viewpoint. This often results in large changes in the object's appearance. This recognition problem is made difficult by the great variability in head rotation and tilt, lighting intensity and angle, facial expression, aging, etc.

Some other attempts at facial recognition by machine have allowed for little or no variability in these quantities.

1.2 Fundamentals of Digital Image Processing:

Digital image processing is a subset of the electronic domain wherein the image is converted to an array of small integers, called *pixels* (derived from *picture element)*, representing a physical quantity such as scene radiance, stored in a digital memory, and processed by computer or other digital hardware. Digital image processing, either as enhancement for human observers or performing autonomous analysis, offers advantages in cost, speed, and flexibility, and with the rapidly falling price and rising performance of personal computers it has become the dominant method in use.

An image is denoted by two dimensional functions of the form $f(x,y)$. The value or amplitude of f at spatial coordinates (x,y) is a positive scalar quantity whose physical meaning is determined by the source of the image. In a digital image, (x,y), and the magnitude of f are all finite and discrete quantities.

It is a hard task to distinguish between the domains of image processing and any other related area such as computer vision. But the two areas are quite different in the kind of output we get from them. **Computer vision** is the science and technology of machines that see. As a scientific discipline, computer vision is concerned with the theory for building artificial systems that obtain information from images. The image data can take many forms, such as a video sequence, views from multiple cameras, or multi-dimensional data from a medical scanner. In computer vision, the input is a digital image and the output is some representation of its interesting features. Image processing is often used in computer vision as a pre-processing step. Image processing is defined as an area when both input and output are images.

As a technological discipline, computer vision seeks to apply the theories and models of computer vision to the construction of computer vision systems.

The organization of a computer vision system is highly application dependent. Some systems are stand-alone applications which solve a specific measurement or detection problem, while other constitute a sub-system of a larger design which, for example, also contains sub-systems for control of mechanical actuators, planning, information databases, man-machine interfaces, etc. The specific implementation of a computer vision system also depends on if its functionality is pre-specified or if some part of it can be learned or modified during operation. There are, however, typical functions which are found in many computer vision systems.

1.3 PROBLEM DEFINATION:

Facial Expression Detection means finding the Expression of an image and recognize the which expression it is such as Happy, Sad, Angry, Disgust, Neutral etc. The technique used for Facial Expression Detection is Principal Component Analysis. The Principal Component Analysis (PCA) is one of the most successful techniques that have been used to recognize faces in images.

The proposed method was carried out by taking the picture database. The database was obtained with 10 photographs of each person at different expressions. These expressions can be classified into some discrete classes like happy, anger, disgust, sad and neutral. Absence of any expression is the “neutral” expression. There are 30 persons in database. The database is kept in the train folder which contains each person having all his/her photographs.

Another database was also prepared for testing phase by taking 5 photographs of 30 persons in different expressions and viewing angles but in similar conditions (such as lighting, background, distance from camera etc.). And these database images were stored in test folder.

1.4 THESIS LAYOUT:

CHAPTER 1 Explained about the fundamentals of digital image processing and problem definition.

CHAPTER 2 Biometrics Technology and Various types of Biometrics.

CHAPTER 3 This chapter contains proposed Principal Component Analysis technique and overview of the proposed system.

CHAPTER 4 This chapter contains the Implementation of facial expression detection.

CHAPTER 5 This chapter contains the results of the proposed technique.

CHAPTER 6 This chapter contains the conclusion and future work that can be done.

Chapter 2

2.1 Biometrics:

What is Biometrics?

The study of automated identification, by use of physical or behavioural traits. [2]

Physical vs. Behavioural:

- **Physical**
  - Fingerprint
  - Iris
  - Ear
  - Face
  - Retina
  - Hands
- **Behavioral**
  - Signature
  - Walking gait
  - Typing patterns
- **Both**
  - Voice

Why go for Biometrics?

- **Authentication** – the process of verifying that a user requesting a network resource is who he, she, or it claims to be, and vice versa.
- **Conventional authentication methods**
  - **something that you have** – key, magnetic card or smartcard
  - **something that you know** – PIN or password
- **Biometric authentication uses personal features**
  - something that you are

Advantages:

Biometrics has no risk of

- Forgetting it
- Loosing it
- Getting it stolen
- Getting it copied
- Being used by anyone else.

Essential Properties of a Biometric

- **Universal**
  - Everyone should have the characteristic
- **Uniqueness**
  - No two persons have the same characteristic
- **Permanence**
  - Characteristic should be unchangeable
- **Collectability**

  Characteristic must be measurable

Biometric System Process Flow

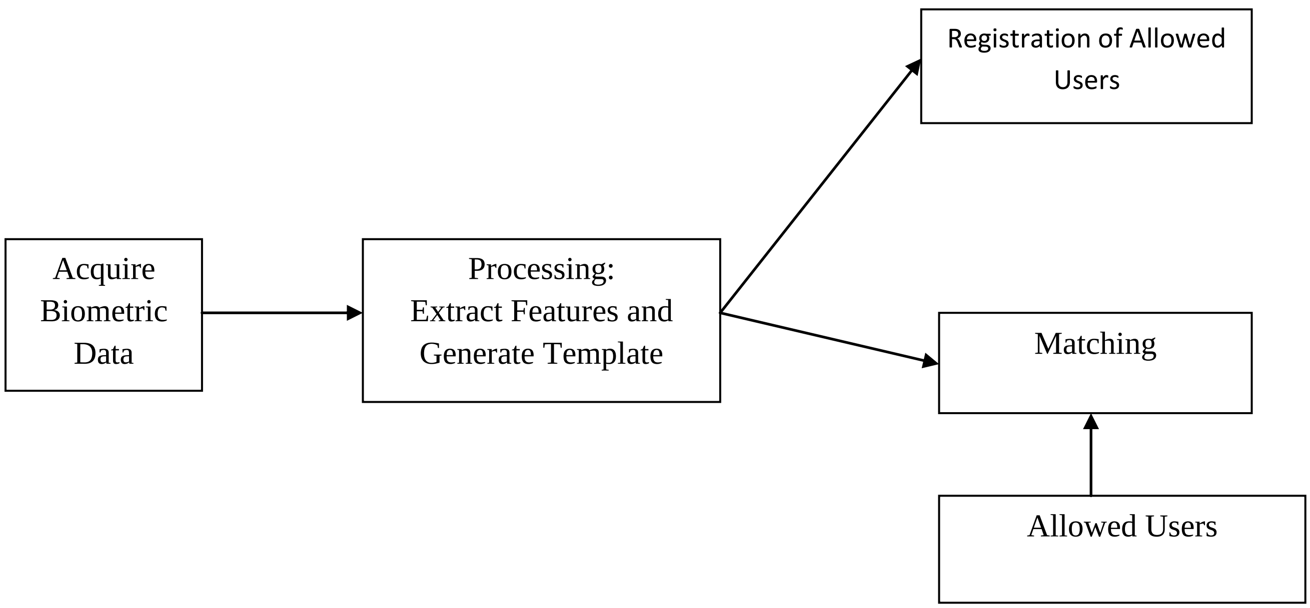


Fig 2.1 : Biometric System Process Flow

Pattern Recognition:

- Description and classification of measurements taken from physical or mental processes
- Examination of pattern characteristics
- Formulation of the recognition system
- Important part of any biometric system

2.2 Types of Biometrics:

2.2.1 FACE RECOGNITION:

In general, face recognition techniques can be divided into two groups based on the face representation they use.

1) Appearance-based which uses a holistic texture features and is applied to either whole face or specific regions in a face image.
2) Feature-based which use geometrical facial features (mouth, eyes, cheeks, etc..) and geometric relationships between them.

The identification of a person by their facial image can be done in number of different ways such as by capturing an image of the face in the visible spectrum using an inexpensive camera or by using the infrared patterns of facial heat emission. Facial recognition in visible light typically model key features from the central portion of a facial image. Using a wide assortment of cameras, the visible light systems extract features from the captured images that do not change over time while avoiding superficial features such as facial expressions or hair. Several approaches to modelling facial images in the visible spectrum are Principal Component Analysis, Local Feature Analysis, neural networks, elastic graph theory, and multi resolution analysis.

2.2.2 FINGERPRINTS:

One of the most commercially available biometric technologies, fingerprint recognition devices for desktop and laptop access are now widely available from many different vendors at low cost. Finger prints are unique for each finger of a person including identical twins. With these devices, users no longer need to type passwords instead, only a touch provides instant access. Fingerprint systems can also be used in identification mode.

Why Fingerprint biometry?

- **High Universality**
    - A majority of the population (>96%) have legible fingerprints.
    - More than the number of people who possess passports, license and IDs.
- **High Distinctiveness**
    - Even identical twins have different fingerprints (most biometrics fail).
    - Individuality of fingerprints established through empirical evidence.
- **High Permanence**
    - Fingerprints are formed in the fetal stage and remain structurally unchanged through out life.
- **High Performance**
    - One of the most accurate forms of biometrics available.
    - Best trade off between convenience and security.
- **High Acceptability**
    - Fingerprint acquisition is non intrusive. Requires no training.

Advantages:

- Uniqueness.
- Surety over the Cards and Keypads.
- Against to Cards Duplication, misplacement and improper disclosure of password.
- No excuses for RF/Magnetic Cards forget ness.
- No need to further invest on the Cards Cost.
- No need to further manage the Cards Writing Devices.

2.2.3 SIGNATURE VERIFICATION:

The technology is based on measuring speed, pressure and angle used by the person when a signature is produced. This technology uses the dynamic analysis of a signature to authenticate a person. One focus for this technology has been e-business applications and other applications where signature is an accepted method of personal authentication.

2.2.4 IRIS RECOGNITION:

Iris recognition is a method of biometric authentication that uses pattern recognition techniques based on high resolution images of the irides of an individual’s eyes. This recognition method uses the iris of the eye, which is the colored area that surrounds the pupil. The technology works well in both verification and identification modes. Current systems can be used even in the presence of eyeglasses and contact lenses. It does not require physical contact with a scanner. The technology is not intrusive.

2.2.5 SPEAKER RECOGNITION:

Speaker recognition uses the acoustic features of speech that have been found to differ between individuals. These acoustic patterns reflects both anatomy (example, size and shape of the throat and mouth) and learned behavioural patterns (example, voice pitch, speaking style). Speaker recognition systems employ three styles of spoken input: text dependent, text prompted, text independent. Most speaker verifications applications uses text dependent input, which involves selection and enrolment of one or more voice passwords. Text prompted input is used whenever there is concern of imposters. Voice changes due to aging also need to be addressed by recognition systems. The technology needs little additional hardware by using existing microphones and voice- transmission technology allowing recognition over long distances via ordinary telephones.

In this project we focussed on facial expression detection (face recognition) approach out of these biometric approaches. For facial expression detection we use Principal Component Analysis. Description of that is given in following pages.

Chapter 3

FACIAL EXPRESSION DETECTION USING PCA

3.1 FACE SPACE AND ITS DIMENSIONALITY:

Computer analysis of face images deals with a visual signal (light reflected of the surface of a face) that is registered by a digital sensor as an array of pixel values. The pixels may encode color or only intensity. After proper normalization and resizing to a fixed m-by-n size, the pixel array can be represented as a point (i.e. vector) in an mn-dimensional image space by simply writing its pixel values in a fixed order. A critical issue in the analysis of such multi-dimensional data is the dimensionality, the number of coordinate necessary to specify a data point.

3.2 IMAGE SPACE VS FACE SPACE:

In order to specify an arbitrary image in the image space, one needs to specify every pixel value. "Thus nominal" dimensionality of the space, dictated by the pixel representation, is mn-a very high number even for images of modest size however, much of the surface of a face is smooth and has regular texture.

Therefore, per-pixel sampling is in fact unnecessarily dense. The value of a pixel is typically highly correlated with the values of the surrounding pixels. Moreover, the appearance of faces is highly constrained, for example, any frontal view of a face is roughly symmetrical, has eyes on the sides, nose in the middle, etc. A vast proportion of the points in the image space does not represent physically possible faces. Thus the natural constraints dictate that the face images will in fact be confined to a subspace, which is referred to as the face space.

3.3 PRINCIPAL COMPONENT ANALYSIS:

Principal Component Analysis is a standard technique used in statistical pattern recognition and signal processing for data reduction and Feature extraction. Principal Component Analysis (PCA) is a dimensionality reduction technique based on extracting the desired number of principal components of the multi-dimensional data. The purpose of PCA is to reduce the large dimensionality of the data space (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables), which are needed to describe the data economically. This is the case when there is a strong correlation between observed variables. The first principal component is the linear combination of the original dimensions that has the maximum variance;

the n-th principal component is the linear combination with the highest variance, subject to being orthogonal to the n -1 first principal components.

For example, face image from the database with size 112×92 can be considered as a vector of dimension 10,304, or equivalently a point in a 10,304 dimensional space. An ensemble of images maps to a collection of points in this huge space. Images of faces, being similar in overall configuration, will not be randomly distributed in this huge image space and thus can be described by a relatively low dimensional subspace. The main idea of the principle component is to find the vectors that best account for the distribution of face images within the entire image space. These vectors define the subspace of face images, which we call “face space”.

PCA is an information theory approach of coding and decoding face images may give insight into the information content of face images, emphasizing the significant local and global "features". Such features may or may not be directly related to face features such as eyes, nose, lips, and hair.

In the language of information theory, we want to extract the relevant information in a face image, encode it as efficiently as possible, and compare one face encoding with a database of models encoded similarly. A simple approach to extracting the information contained in an image of face is to somehow capture the variation in a collection of images, independent of any judgment of features, and use this information to encode and compare individual face images.

These eigenvectors can be thought of as a set of features that together characterize the variation between face images. Each image location contributes more or less of each eigen vector, so that we can display the eigenvector as a sort of ghostly face which we call an ***eigenface***.

Each individual face can be represented exactly in terms of a linear combination of the eigenfaces. Each face can also be approximated using only the "best" eigenfaces-those that have the largest eigenvalues and which therefore account for the most variance within the set of face images. The best M eigenfaces span an M-Dimensional subspace- "face space" – of all possible images.

This approach of expression detection involves the following initialization operations:

- Acquire the intial set of face images (the training set).

- Calculate the eigenfaces from the training set, keeping only the M images that correspond to the highest eigenvalues. These M images define the face space. As new faces are experienced; the eigenfaces can be up-dated or recalculated.
- Calculate the corresponding distribution in M-dimensional weight space for each known individual, by projecting his or her face images onto the "face space".

3.4 TRAINING STEP:

Images of faces, being similar in overall configuration, will not be randomly distributed in the huge space and thus can be distributed by a relatively low dimensional subspace. The main idea of principal component analysis is to find the vectors that best account for the distribution of face images within the entire image space. These vectors define the subspace of face images, which we call "face space". Each vector is of length N square, describes an N-by-N image, and is a linear combination of original face images, and because they are face-like in appearance, we refer then to as "eigenfaces".

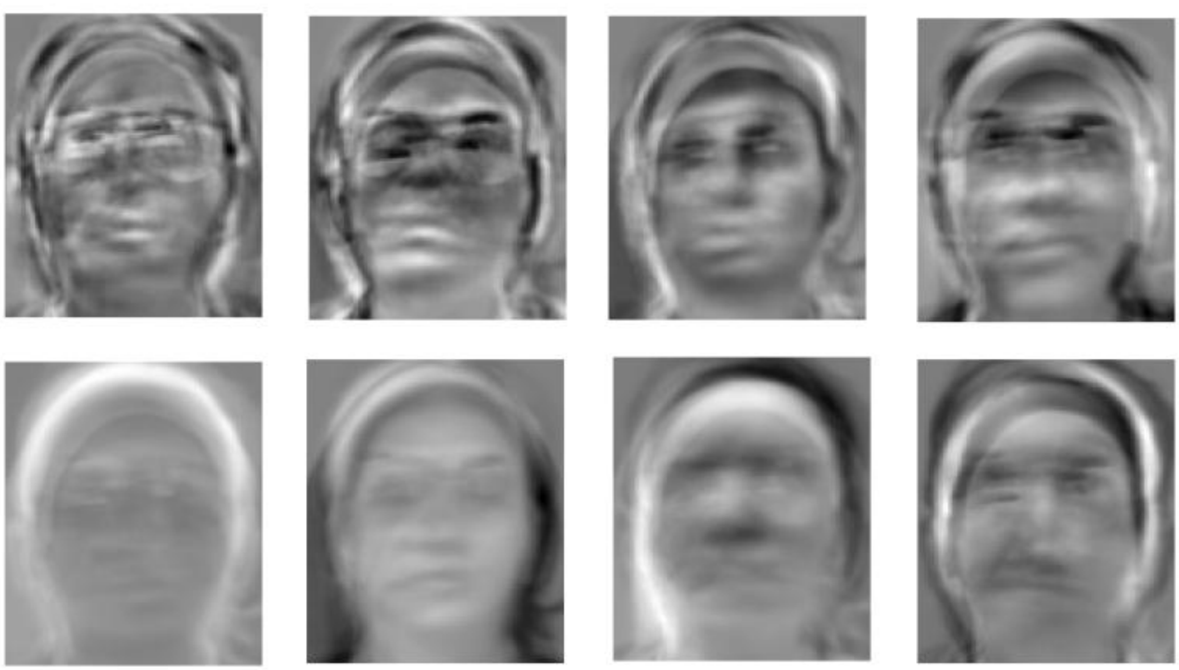
1. Let the training set of M face images be Γ1, Γ2, …, ΓM. The average (mean) face of the training set is defined by

The Average Face

2. Each face differs from the average face by the vector

Example of

Example of



3.1 Example of Eigenfaces

3. We shall rearrange these vectors in a matrix A= of dimensions N by M, which will then subjected to the PCA.

4. The next goal is to find a set of M-1 orthogonal vectors , which best describes the distribution of the input data in a least-squares sense, i.e., the Euclidian projection error is minimized. We start by finding the covariance matrix.

................1

Where the matrix A= . The matrix C, however, is N by N , and determining the N square eigenvectors and eigen values is an intractable task for typical image sizes. We need a computationally feasible method to find these eigenvectors. If the number of data points in the image space is less then the dimension of the space (M<N), there will be only M–1,rather than N, meaningful eigenvectors. (The remaining eigenvectors will have associated eigenvalues of zero). Fortunately we can solve for the N2 dimensional eigenvectors in case by first solving for the eigenvectors of an M-by-M matrix – e.g., solving a 16 x 16 matrix rather than a 16,384 x 16,384 matrix and then taking appropriate linear combinations of the face images. Consider the eigenvectors of A such that

A = ...2

Premultiplying both sides by A then we have

A = ...3

From which we see that are the eigen vectors of

C= 4

Following this analysis, we can construct the M by M matrix L = ,where and find the M eigen vectors of L. And these vectors determine linear combinations of the M training set face images to from the eigenfaces .

= 5

With this analysis the calculations are greatly reduced, from the order of the number of pixels in images (N2) to the order of the number image in the training set (M).The associated eigenvalues allow us to rank to eigenvectors according to their usefulness in characterizing the variation among the images.

3.5 RECOGNITION STEP:

After creating the eigenspace we can proceed to recognition using eigenfaces. Given a new image of an individual Γ, the pixels are concatenated the same way as the training images were, the mean image Ψ is subtracted and the result is projected into the face space:

.............6

for k=1,..,M. These calculated values of ω together form a vector that describes the contribution of each eigenface in representing the input face image. In face, this is the projection of an unknown face into the face space. Ω is then used to establish which of the predefined face classes best describes the new face. The simplest way to determine which face class provides the best description of the input face image is to find the face class k that minimizes the Euclidian distance:

..................7

Where is a vector describing the face class. The expression is classified as belonging to a certain class when the minimum (i.e. the maximum matching score)

3.6 EIGEN FACES FOR EXPRESSION DETECTION:

Eigen Faces are used to classify facial expression. It has been assumed that, facial expression can be classified into some discreet classes (like anger, happiness, disgust or sadness) whereas:

1. Absence of any expression is the "Neutral" expression.
2. Intensity of a particular expression can be identified by the level of its "dissimilarity" from the Neutral expression.

Representing the facial expressions in this way has several advantages. Firstly several kinds of expressions can be represented using only two types of information (**1.** class that an expression belongs to and **2.** intensity of the expression). Secondly, it is possible to identify an expression as a mixture of two or more expressions (such as 60% anger, 20% disgust and 20% sad etc.).

To summarize the eigenfaces approach to the facial expression detection involves the following steps:

.

- Firstly, the train images are utilized to create a low dimensional face space. This is done by performing Principal Component Analysis (PCA) in the training image set and taking the principal components (i.e. Eigen vectors with greater Eigen values). In this process, projected versions of all the train images are also created.
- Secondly, the test images also projected on face space.
- Thirdly, the Euclidian distance of a projected test image from all the projected train images are calculated and the minimum value is chosen in order to find out the train image which is most similar to the test image.
- Fourthly, in order to determine the intensity of a particular expression, its Euclidian distance from the mean of the projected neutral images is calculated.

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Chapter 4

IMPLEMENTATION

4.1 IMPLEMENTATION OF EXPRESSION DETECTION USING PCA:

The entire sequence of training and testing is sequential and can be broadly classified as consisting of following two steps:

1. Database Preparation
2. Training
3. Testing

The steps are shown below.

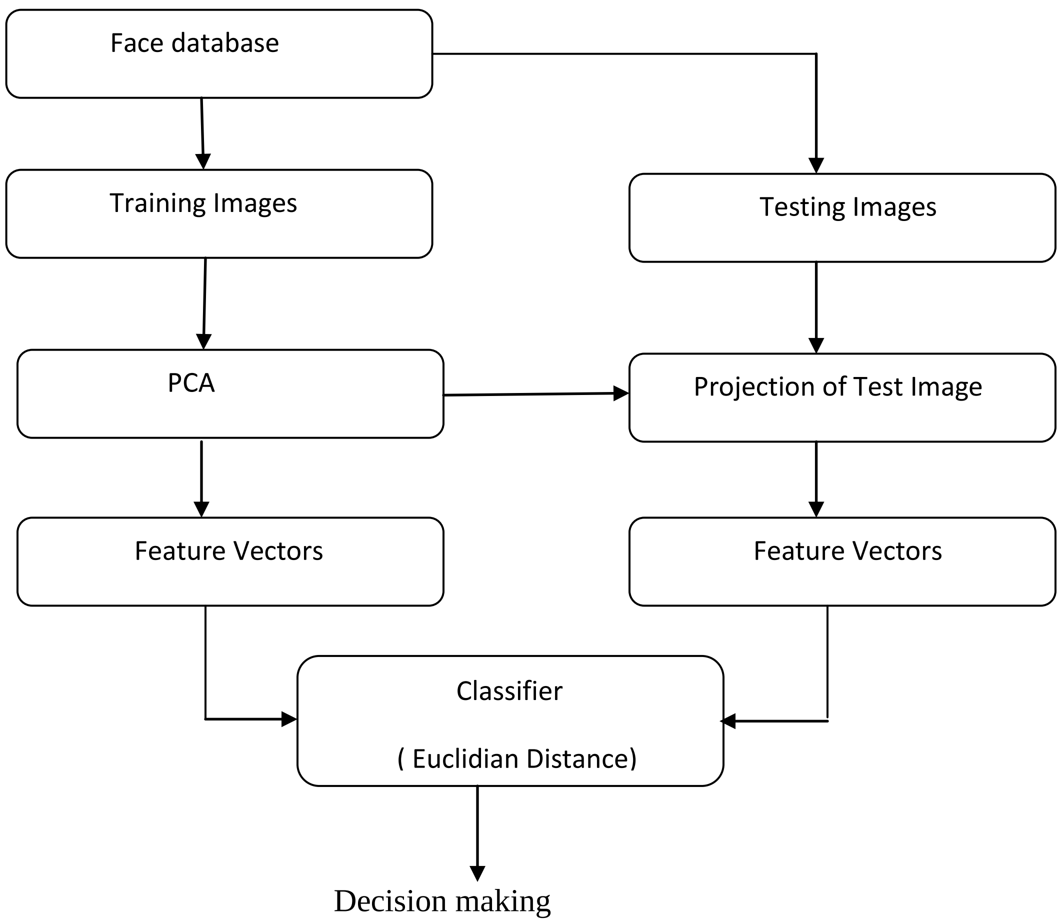


Fig 4.1 Overview of the Proposed System

4.2 DATABASE PREPARATION:

The database was obtained with 15 photographs of each persons at and different expressions, different viewing angels. There are 28 persons in database. The Database is kept in the train folder which contains subfolders for each person having all his/her photographs.

Database was also prepared for testing phase by taking 4-5 photographs of 10 persons in different expressions and viewing angles but in similar conditions (such as lighting, background, distance from camera etc.) using a low resolution camera. And these images were stored in test folder.

Picture Database:

Since the main purpose of this project is facial expression recognition , therefore, the sample pictures are taken under special consideration to ease up the face detection process. Each picture is taken under the condition that, only face is the largest skin colored continuous object in the frame. There are two sets of pictures. One is used for training purpose and another is used for testing. The pictures are classified in the following expressional classes.

1. Image01 to Image09 = Happy
2. Image10 to Image18 = Disgust
3. Image19 to Image27 = Anger
4. Image28 to Image36 = Sad
5. Image37 to Image42 = Neutral

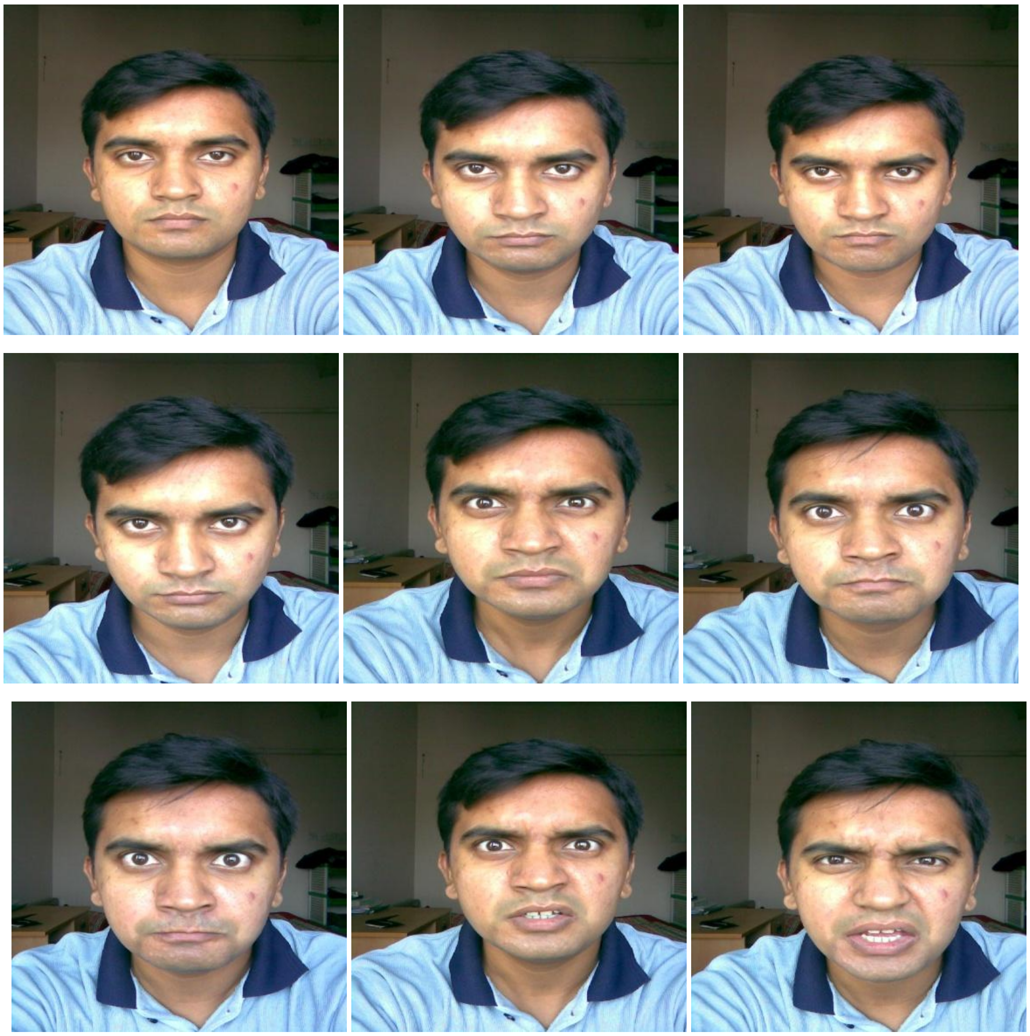
Another image set is used for testing purpose. These images are taken in quite an arbitrary fashion. It also includes some expressions that are not contained in the training set.

The following images are some examples for the different classes of expression

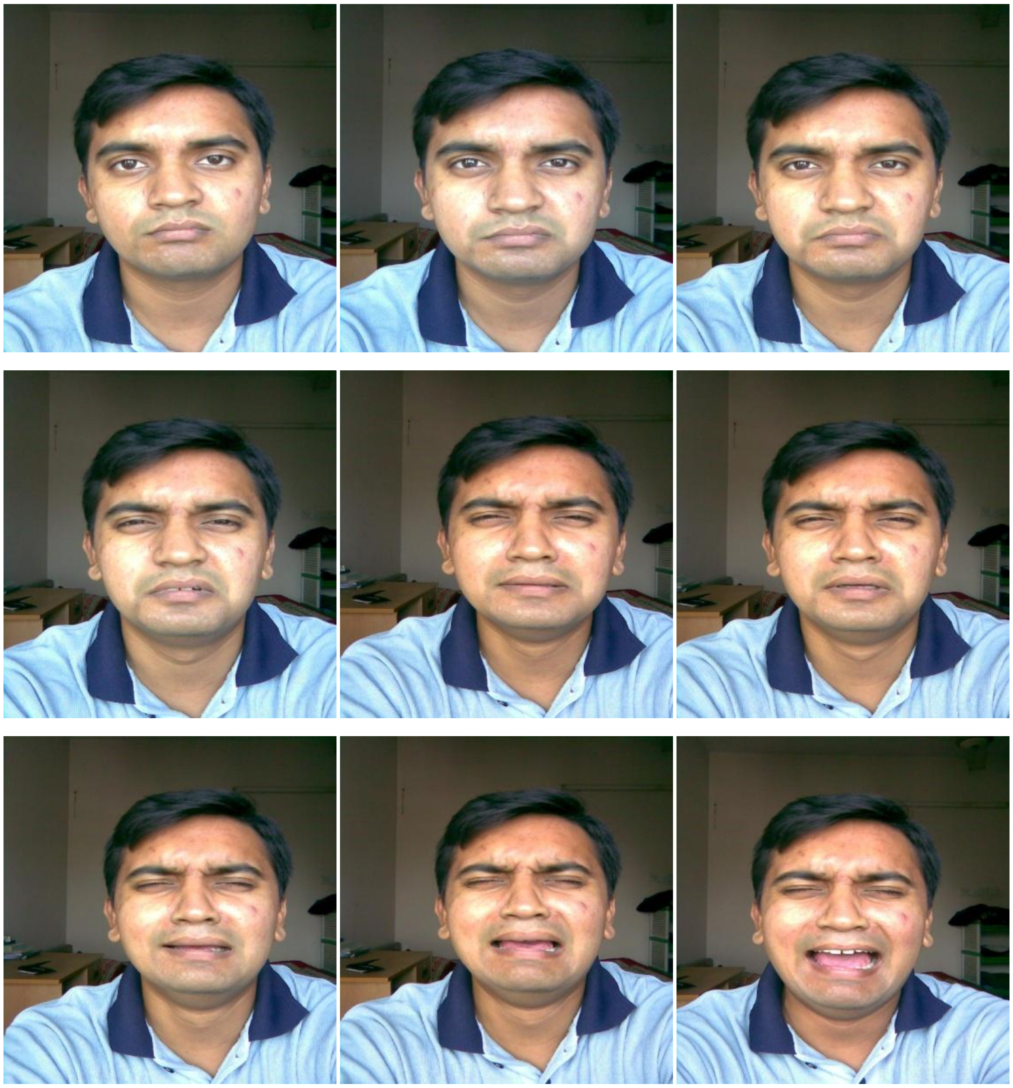
HAPPY:

DISGUST:

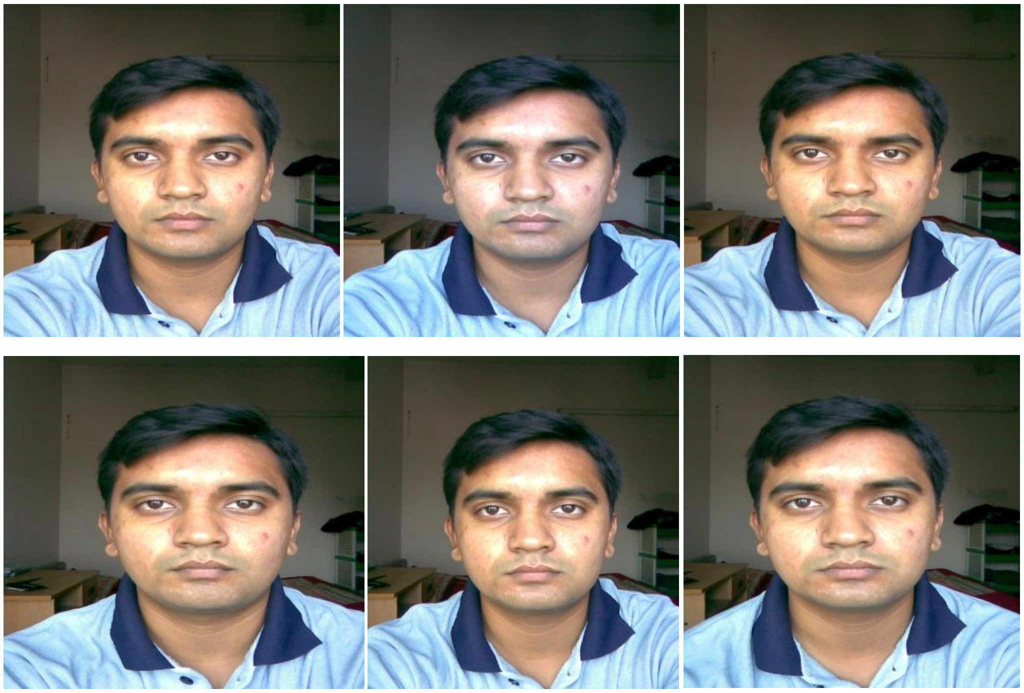
ANGER:



SAD:

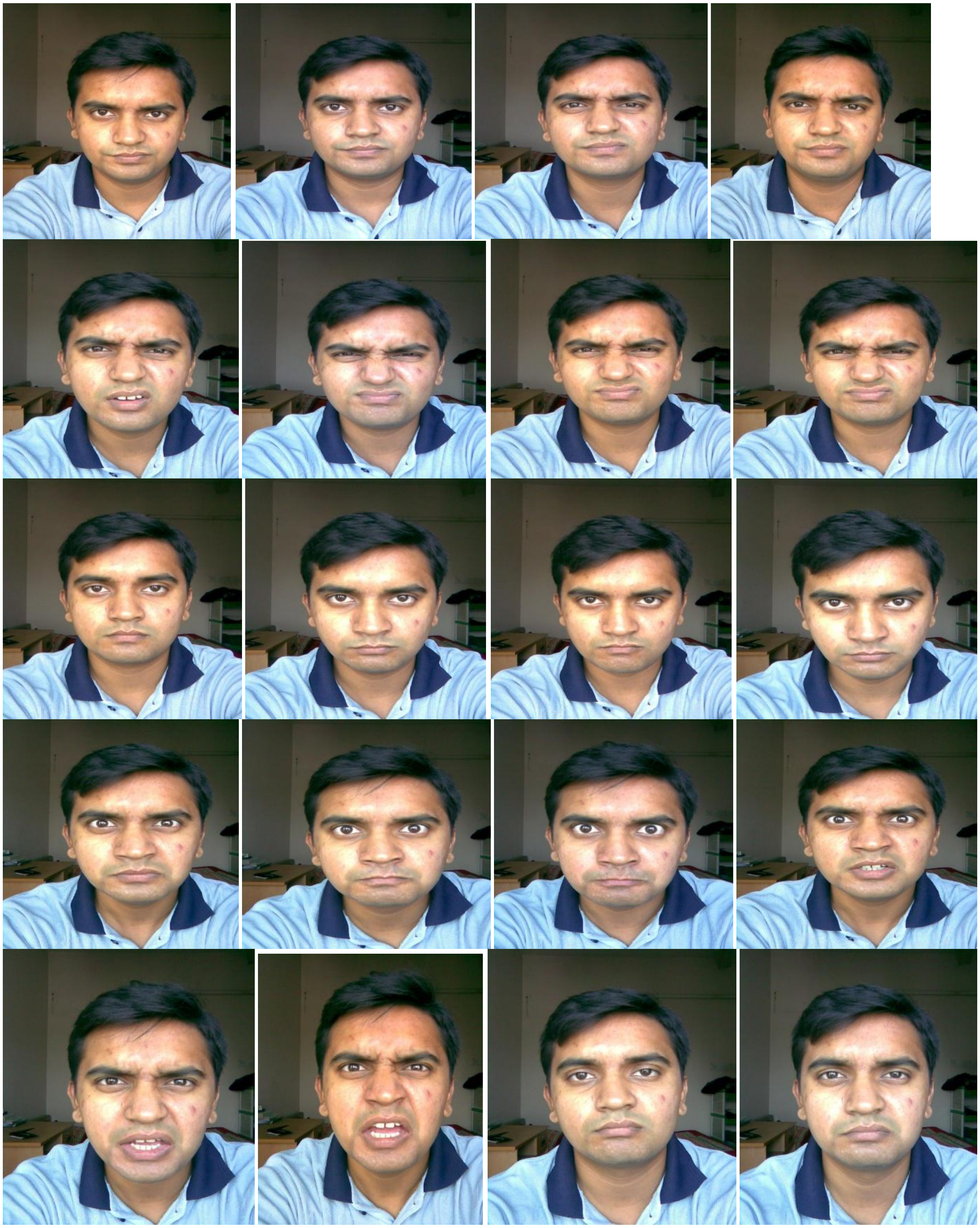


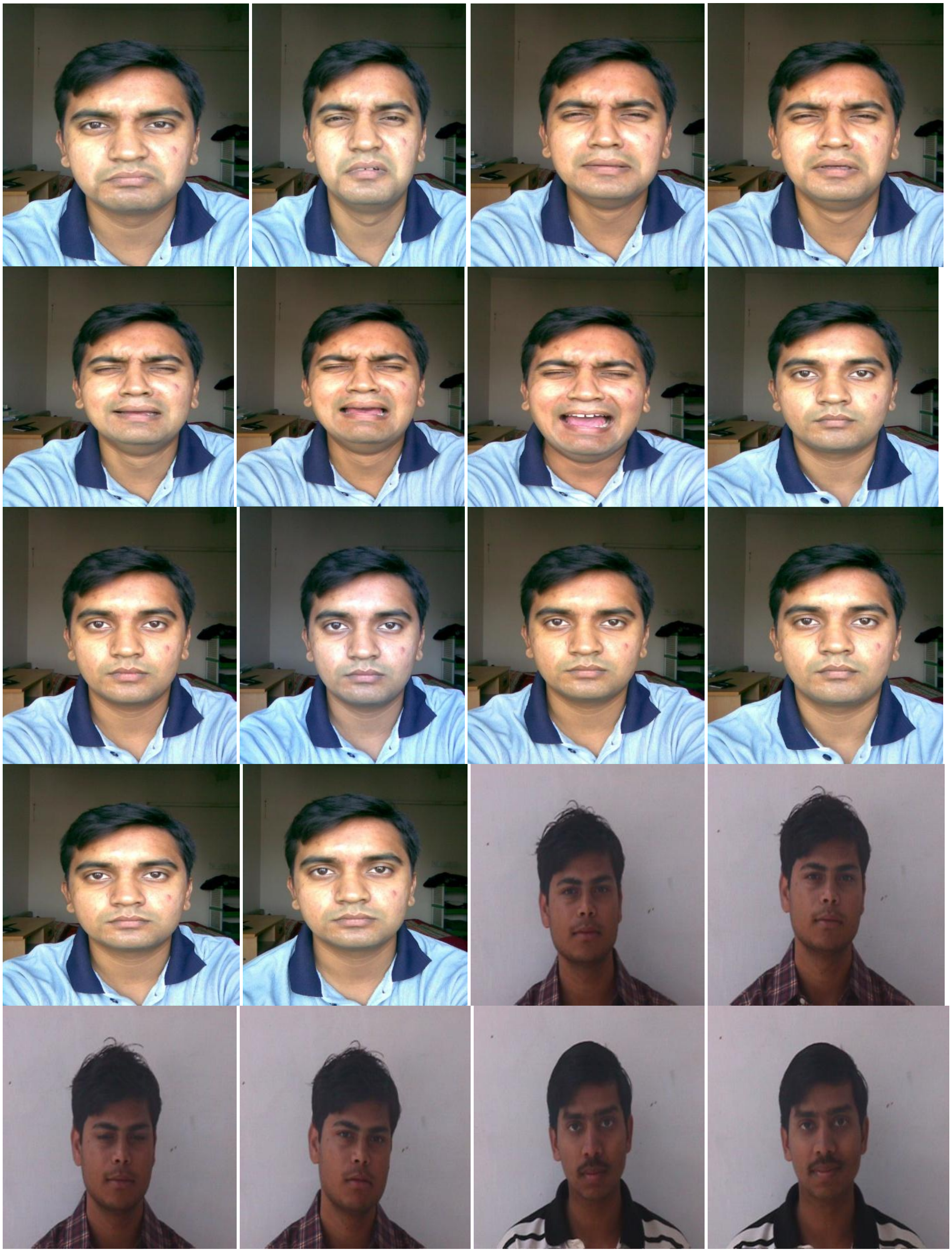
NEUTRAL:

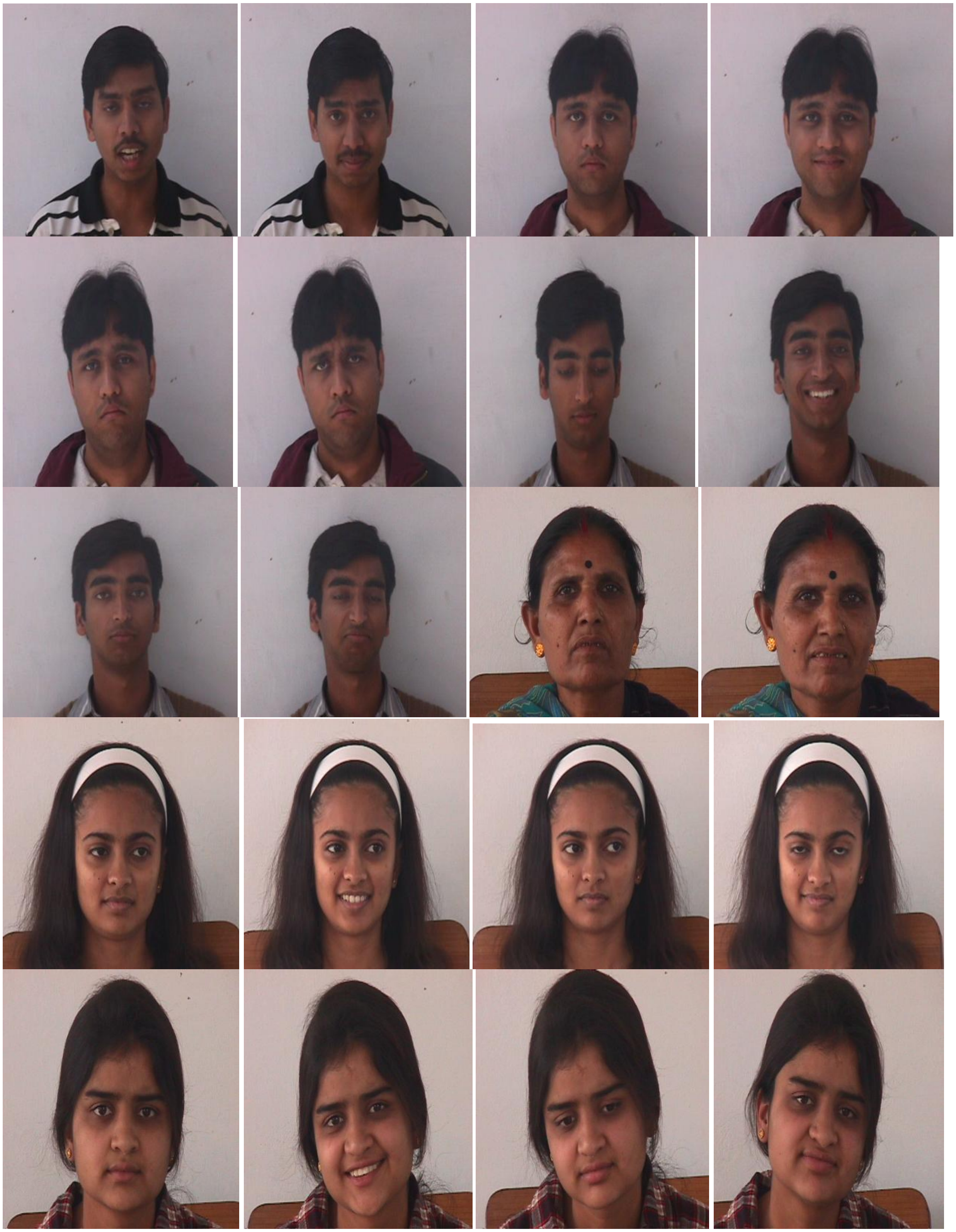


TRAINING DATABASE:

The following database has numbering from Image001 to Image084 respectively used for training purpose and these characteristics are given in results table.

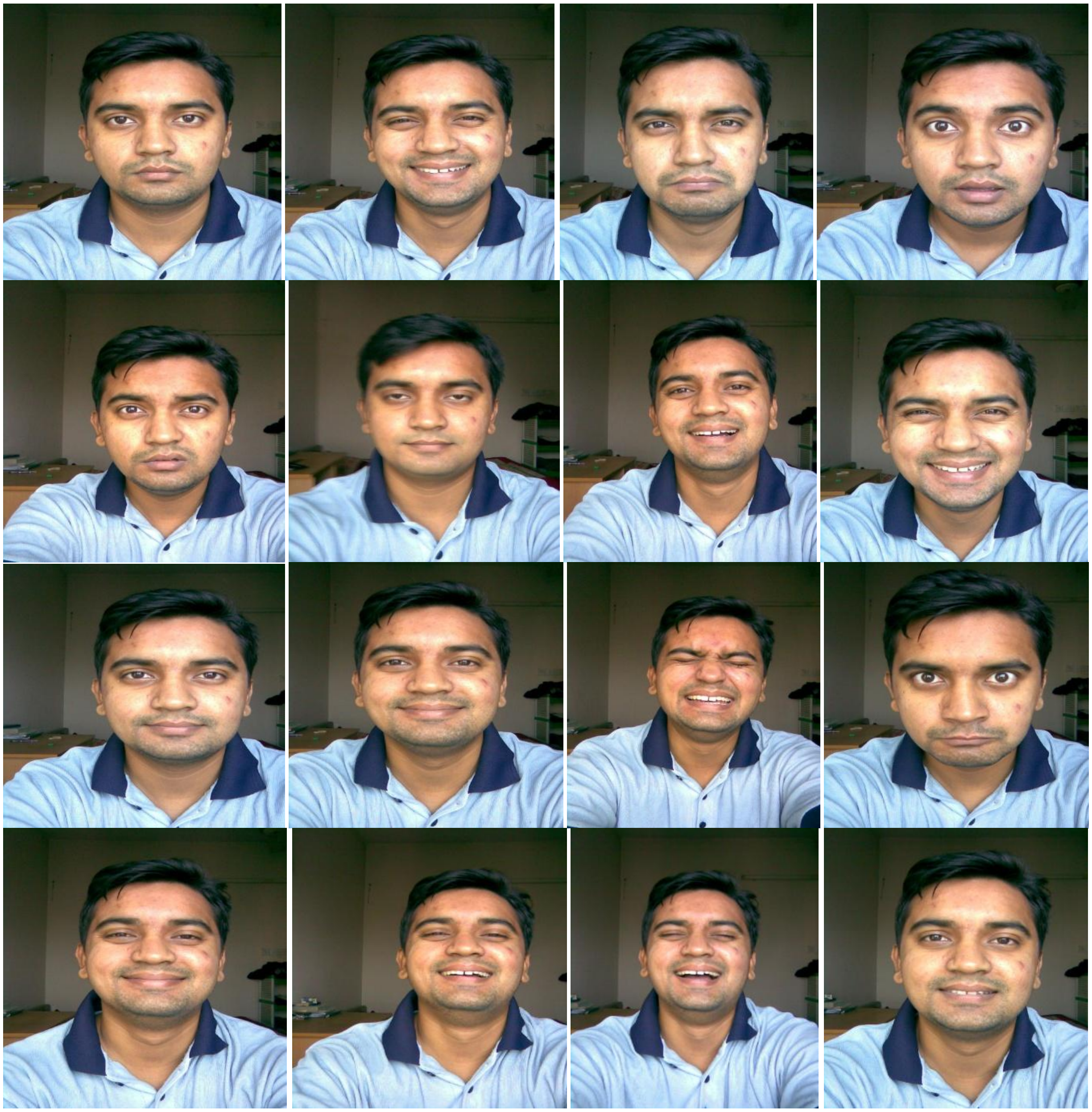


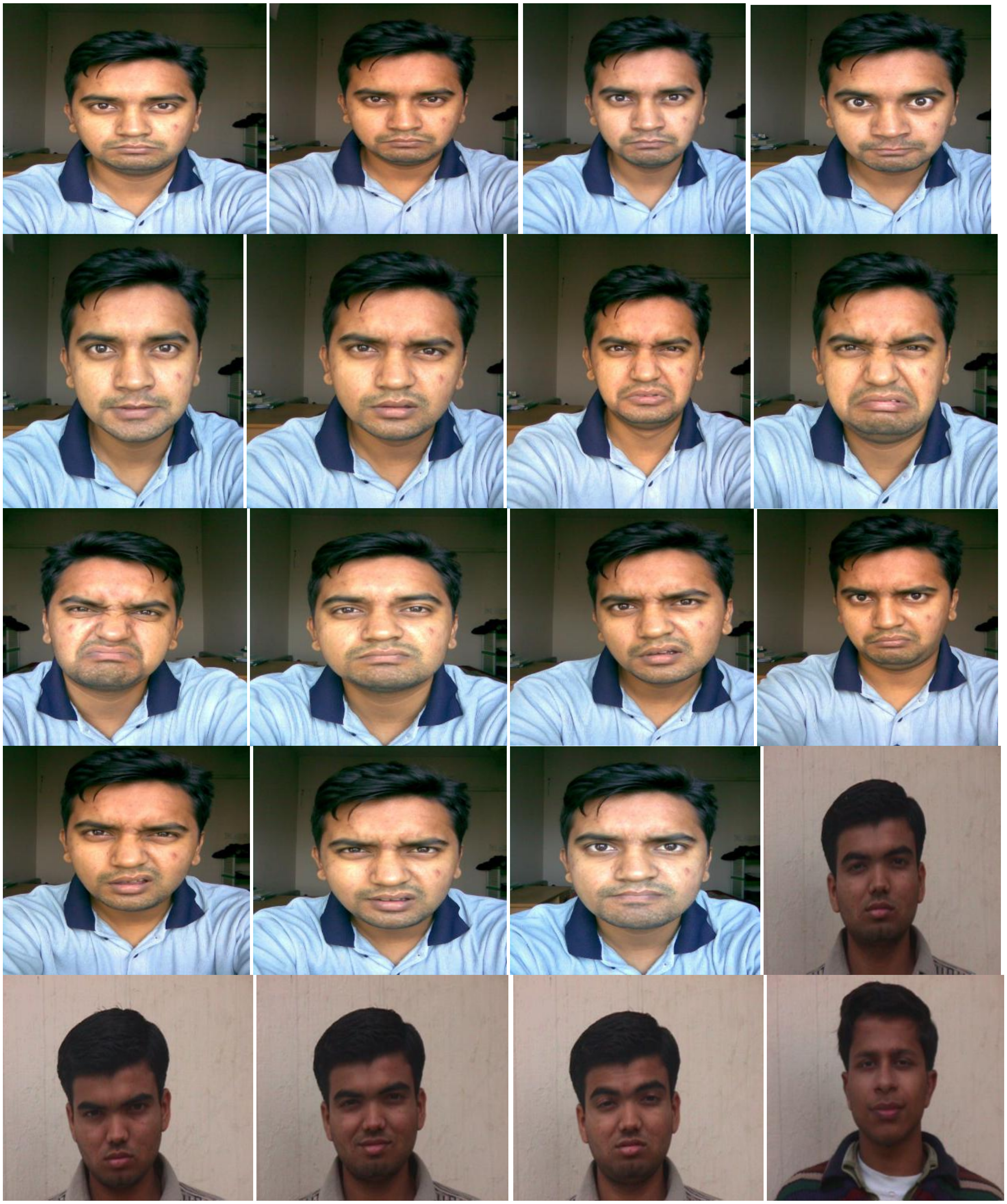


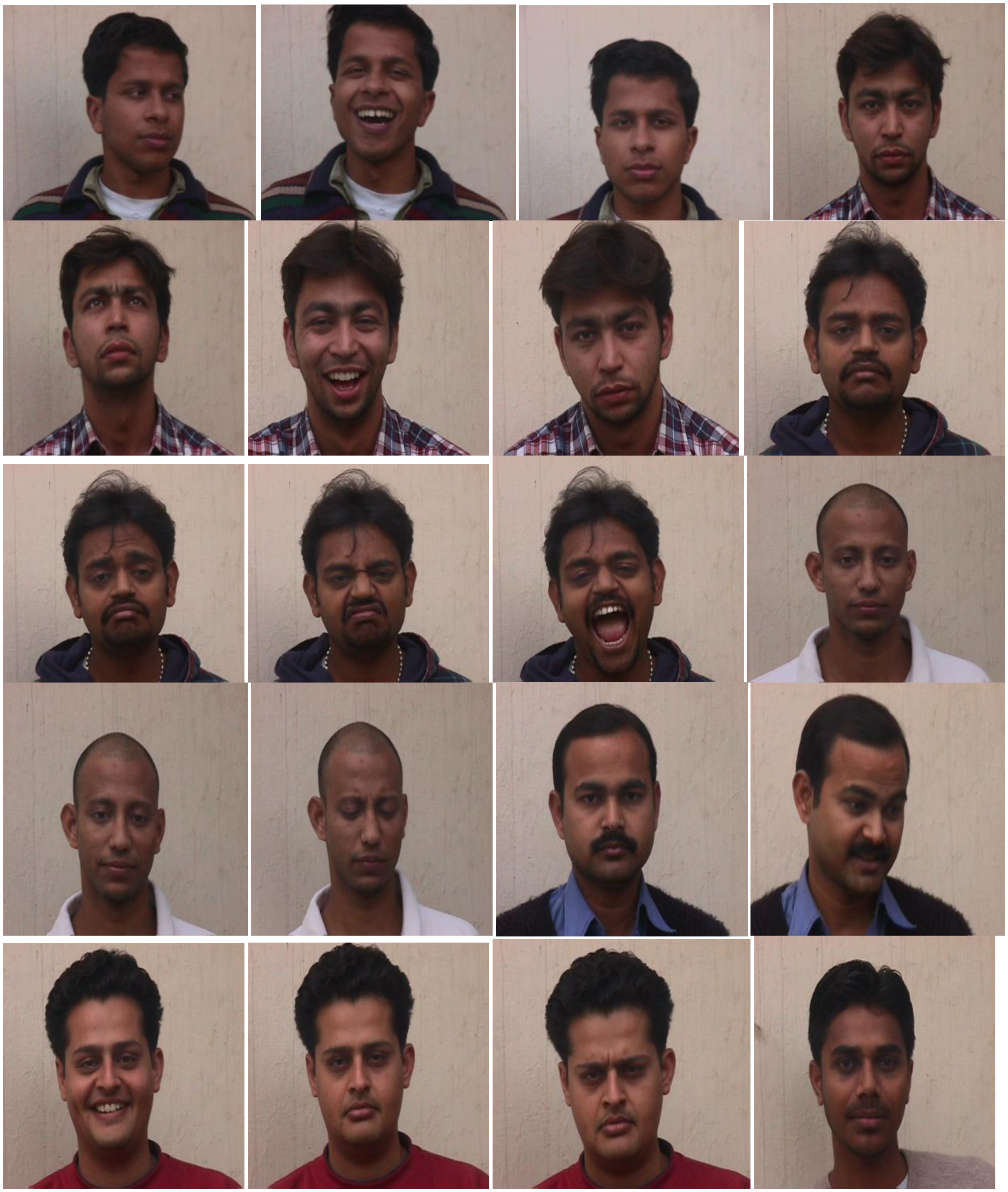


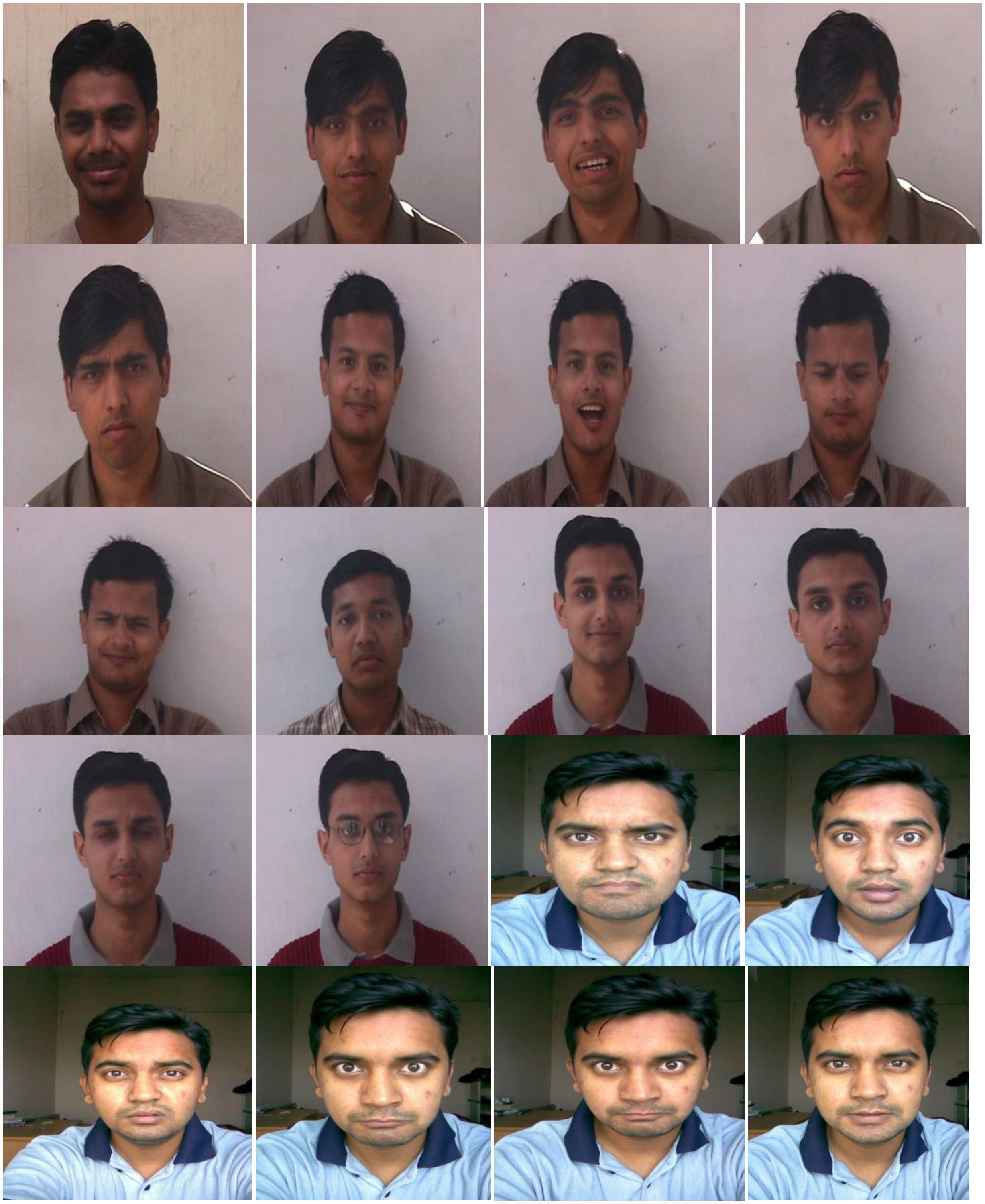
TESTING DATABASE:

The following database has numbering from Image001 to Image083 respectively is used for the testing and the results for this database were given in the below results table.



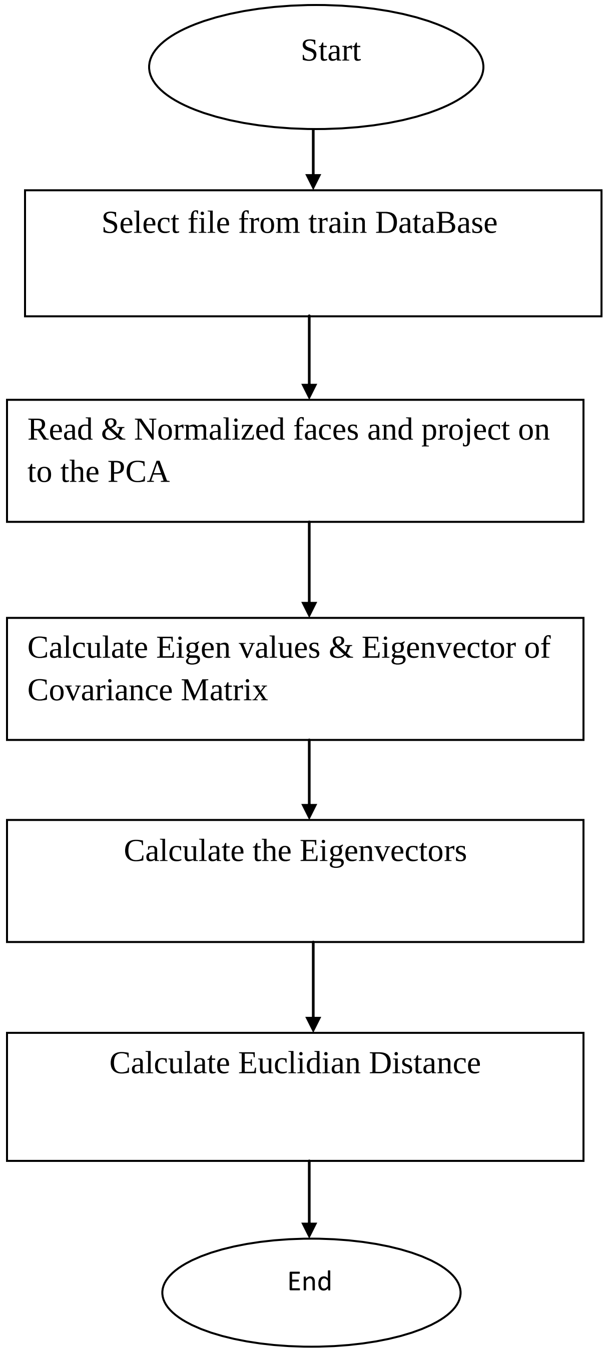






4.3 TRAINING:

1. Select any one (.jpg) file from train database using open file dialog box.
2. By using that read all the faces of each person in train folder.
3. Normalize all the faces.
4. Apply Principal Component Analysis (PCA) to the training image database which will calculate the eigenvalues and eigenvectors of the covariance matrix.
5. Hence calculate the Eigenvectors of Covariance Matrix.
6. Calculate the Euclidian distance.



4.2 Flowchart for Training

4.4 TESTING:

1. Select an image which is to be tested using open file dialog box.

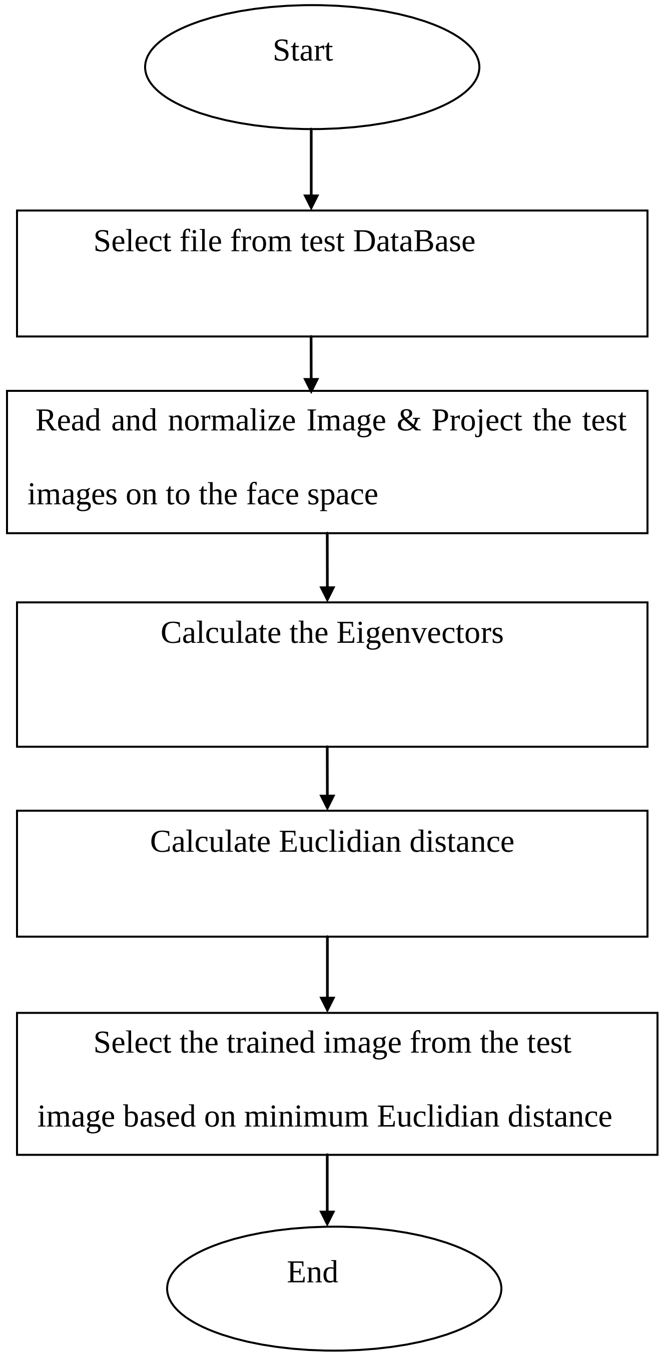
2. By using that read all the faces of each person in test folder.

3. Project the test images on to the face space as a result, all the test images are represented in terms of the selected principal components.

4. The Euclidian distance of all the projected test image from all the train images are calculated.

5. And the minimum value is chosen in order to find out the train image which is most similar to the test image.

6. The test image is assumed to fall in the same class that the closest train image belongs to.



4.3 Flow Chart for testing

4.5 APPLICATIONS:

1. SMART CARDS:

- Drivers’ Licenses
- Passports
- Voter Registrations
- Welfare Fraud
- Voter Registration

2. INFORMATION SECURITY:

- TV Parental control
- Desktop Logon
- Personal Device Logon
- Database Security
- Medical Access
- Internet Access

3. ENTERTAINMENT:

- Video Game
- Virtual Reality
- Training Programs
- Human-Computer-Interaction
- Human-Robotics
- Family Photo Album

4. LAW ENFORCEMENT & SURVEILLANCE:

- Advanced Video surveillance
- Drug Trafficking
- Portal Control

5. ACCESS CONTROL:

- ATM
- Airport

6. SOME COMMERCIAL APPLICATIONS:

- Motion Capture for movie special effects.
- Face Recognition biometric systems.
- Home Robotics.

Chapter 5

EXPERIMENTAL RESULTS

In this project first i trained the characteristics of different facial expressions (such as Happy, Disgust, Sad, Neutral, Angry) with the training database. The following table will gives the characteristics of training database.

5.1 TRAINING DATABASE CHARACTERISTICS:

HAPPY	DISGUST	ANGER	SAD	NEUTRAL
Image 001	Image 014	Image 025	Image 035	Image 044
Image 002	Image 015	Image 026	Image 036	Image 045
Image 003	Image 016	Image 027	Image 037	Image 046
Image 004	Image 017	Image 028	Image 038	Image 047
Image 005	Image 018	Image 029	Image 039	Image 048
Image 006	Image 019	Image 030	Image 040	Image 049
Image 007	Image 020	Image 031	Image 041	Image 050
Image 008	Image 021	Image 032	Image 042	Image 051
Image 009	Image 022	Image 033	Image 043	Image 052
Image 010	Image 023	Image 034	Image 055	Image 059
Image 011	Image 024	Image 053	Image 066	Image 063
Image 012	Image 057	Image 054	Image 069	Image 065
Image 013	Image 061	Image 058	Image 072	Image 071
Image 056	Image 067	Image 062	Image 075	Image 073
Image 060	Image 076	Image 068	Image 084	Image 077
Image 064	Image 081	Image 080		
Image 070	Image 082			
Image 074				
Image 078				
Image 079				
Image 083				

After training the images, we are giving the inputs as the test database then the following results were obtained.

5.2 RESULTS FOR TESTING DATABASE:

TEST IMAGE	DISTANCE	BEST MATCH	TRAIN IMAGE
Image 001.jpg	12989	Neutral	Image 049.jpg
Image 002.jpg	13038	Happy	Image 008.jpg
Image 003.jpg	14245	Disgust	Image 014.jpg
Image 004.jpg	13299	Anger	Image 029.jpg
Image 005.jpg	12696	Anger	Image 025.jpg
Image 006.jpg	13048	Happy	Image 003.jpg
Image 007.jpg	11882	Sad	Image 041.jpg
Image 008.jpg	14673	Happy	Image 010.jpg
Image 009.jpg	13167	Neutral	Image 046.jpg
Image 010.jpg	12010	Sad	Image 041.jpg
Image 011.jpg	9706	Sad	Image 039.jpg
Image 012.jpg	12718	Anger	Image 028.jpg
Image 013.jpg	11905	Happy	Image 006.jpg
Image 014.jpg	11373	Happy	Image 012.jpg
Image 015.jpg	10870	Sad	Image 042.jpg
Image 016.jpg	12308	Sad	Image 039.jpg
Image 017.jpg	12439	Disgust	Image 015.jpg
Image 018.jpg	10649	Disgust	Image 022.jpg
Image 019.jpg	11665	Anger	Image 026.jpg
Image 020.jpg	11515	Anger	Image 026.jpg
Image 021.jpg	12624	Anger	Image 029.jpg

TEST IMAGE	DISTANCE	BEST MATCH	TRAIN IMAGE
Image 022.jpg	11755	Disgust	Image 021.jpg
Image 023.jpg	11233	Disgust	Image 015.jpg
Image 024.jpg	11528	Disgust	Image 016.jpg
Image 025.jpg	12124	Disgust	Image 023.jpg
Image 026.jpg	12986	Neutral	Image 049.jpg
Image 027.jpg	10694	Disgust	Image 016.jpg
Image 028.jpg	9909	Neutral	Image 045.jpg
Image 029.jpg	10671	Anger	Image 029.jpg
Image 030.jpg	12709	Anger	Image 026.jpg
Image 031.jpg	13740	Anger	Image 029.jpg
Image 032.jpg	10770	Sad	Image 055.jpg
Image 033.jpg	11901	Sad	Image 072.jpg
Image 034.jpg	11506	Sad	Image 072.jpg
Image 035.jpg	11353	Sad	Image 072.jpg
Image 036.jpg	11063	Sad	Image 069.jpg
Image 037.jpg	11337	Neutral	Image 063.jpg
Image 038.jpg	8694	Disgust	Image 017.jpg
Image 039.jpg	11491	Sad	Image 072.jpg
Image 040.jpg	11935	Sad	Image 069.jpg
Image 041.jpg	10220	Disgust	Image 061.jpg
Image 042.jpg	8234	Happy	Image 064.jpg

TEST IMAGE	DISTANCE	BEST MATCH	TRAIN IMAGE
Image 043.jpg	12686	Happy	Image 064.jpg
Image 044.jpg	11023	Disgust	Image 061.jpg
Image 045.jpg	12188	Disgust	Image 061.jpg
Image 046.jpg	11325	Disgust	Image 061.jpg
Image 047.jpg	11657	Happy	Image 079.jpg
Image 048.jpg	10826	Happy	Image 070.jpg
Image 049.jpg	10264	Sad	Image 072.jpg
Image 050.jpg	10491	Sad	Image 072.jpg
Image 051.jpg	10834	Sad	Image 072.jpg
Image 052.jpg	10483	Disgust	Image 061.jpg
Image 053.jpg	9531	Disgust	Image 061.jpg
Image 054.jpg	10026	Happy	Image 064.jpg
Image 055.jpg	10248	Happy	Image 064.jpg
Image 056.jpg	10840	Disgust	Image 061.jpg
Image 057.jpg	13297	Disgust	Image 057.jpg
Image 058.jpg	11271	Sad	Image 072.jpg
Image 059.jpg	12425	Happy	Image 070.jpg
Image 060.jpg	12223	Sad	Image 072.jpg
Image 061.jpg	12709	Sad	Image 072.jpg
Image 062.jpg	7433	Anger	Image 053.jpg
Image 063.jpg	5928	Disgust	Image 061.jpg

TEST IMAGE	DISTANCE	BEST MATCH	TRAIN IMAGE
Image 064.jpg	5636	Sad	Image 069.jpg
Image 065.jpg	6083	Sad	Image 069.jpg
Image 066.jpg	7926	Neutral	Image 059.jpg
Image 067.jpg	8061	Neutral	Image 051.jpg
Image 068.jpg	7879	Neutral	Image 051.jpg
Image 069.jpg	8478	Neutral	Image 051.jpg
Image 070.jpg	7498	Neutral	Image 051.jpg
Image 071.jpg	13740	Anger	Image 029.jpg
Image 072.jpg	13299	Anger	Image 029.jpg
Image 073.jpg	12696	Anger	Image 025.jpg
Image 074.jpg	12718	Anger	Image 028.jpg
Image 075.jpg	11515	Anger	Image 026.jpg
Image 076.jpg	12624	Anger	Image 029.jpg
Image 077.jpg	10671	Anger	Image 029.jpg
Image 078.jpg	7786	Neutral	Image 063.jpg
Image 079.jpg	7739	Neutral	Image 063.jpg
Image 080.jpg	7007	Neutral	Image 063.jpg
Image 081.jpg	6987	Neutral	Image 063.jpg
Image 082.jpg	8053	Disgust	Image 061.jpg
Image 083.jpg	7426	Neutral	Image 051.jpg

The Principal Components are Coefficient, Score, and Latent. Coefficients are nearly equal to zero and Score and latent for the image database is given in below table.

Score =

1.0e+003 *

Columns 1 through 10

-3.2152	-0.0179	1.8061	-0.7596	0.4986	-0.1272	1.3012	-1.4176	0.2699	-0.0926
-3.6475	-0.6972	2.1162	-0.7883	-0.1241	0.2245	1.8240	-1.1757	-0.7122	-1.9253
-3.1266	0.6589	1.4047	-2.1129	0.0253	-0.4713	1.0070	-0.4527	-0.7251	1.9733
-2.6039	0.7227	0.8050	-1.5799	0.1618	1.3809	-0.8330	1.2499	0.3053	1.2589
-1.9440	0.9984	0.5748	-1.5432	0.4520	3.1964	-0.8477	1.8593	0.4400	-0.9460
3.0943	-1.6956	1.0836	0.0717	-2.7771	1.2822	-2.0096	-1.9295	-0.5644	-0.3701
0.6547	-3.2713	-2.1968	1.1042	-0.1754	-0.5091	1.5665	0.9664	-0.1559	-0.4918
-1.8996	-2.1119	0.4768	1.9361	0.8904	0.3369	-0.2224	0.2976	-0.8266	0.5345
2.2567	-2.2415	-2.7276	-0.3506	-0.4702	1.1062	2.3546	0.7658	0.2636	0.2012
3.2120	-1.4898	-0.2305	0.3923	-1.6216	1.5868	-0.0836	-1.0354	0.7057	1.0804
-1.6922	-1.4760	0.6965	2.5050	1.1415	-0.0222	-0.9566	0.5450	-0.6739	0.2448
4.9958	2.0407	4.4605	1.4713	-1.9657	-1.5239	1.0088	1.9409	-0.0215	-0.0930
5.1922	0.3599	0.1592	-2.4903	2.7144	-0.2484	-0.6298	-0.3870	-0.0888	-0.9569
4.3427	-1.8418	0.4450	-2.2729	2.3557	-1.4600	-0.5444	-0.0536	0.4998	0.5016
2.5104	4.5442	-2.1159	1.7467	1.1614	0.8407	0.5283	-0.7831	-2.5420	0.3399
0.2330	3.3467	-1.6594	0.6386	-0.5448	0.1304	0.8231	-0.6016	2.2229	0.2657
-2.0484	0.9416	-1.4341	-1.3608	-1.0876	-1.8788	-0.3681	-0.6329	0.7941	0.0565

-1.8180	0.4640	-2.6772	-2.4219	-2.4320	-1.7533	-1.2634	1.1502	-1.4423	-0.6033
-2.2199	-0.2708	-0.0887	1.7798	0.6400	-1.2654	-0.9787	-0.1320	0.5806	-0.0683
-1.5822	-0.7244	-0.2549	2.3156	0.6615	-0.9067	-1.0854	-0.0703	0.4001	0.1853
-0.6944	1.7611	-0.6432	1.7190	0.4961	0.0814	-0.5908	-0.1039	1.2707	-1.0950

Columns 11 through 20

0.2381	-0.4727	0.0999	-0.2942	0.6335	-0.0795	0.8053	1.4328	-0.6839	-0.4154
0.7086	0.0306	0.1326	-0.3183	0.1959	0.2525	-0.3302	-1.0450	0.2822	0.4270
-1.4144	0.3194	-0.9004	0.4132	-0.8933	0.6109	-0.7013	0.0089	0.2665	-0.0453
-0.6350	-0.8191	0.5479	-0.1955	1.1887	-0.3552	0.9016	-0.9551	-0.2510	0.2916
0.2577	0.1177	0.4246	-0.4547	-0.8363	-0.1250	-0.6825	0.7075	0.2831	-0.1851
-0.9228	-0.7514	0.8866	0.9052	-0.3625	0.1615	0.0868	0.0445	-0.0166	-0.0679
-2.1558	0.6810	1.1683	-0.9174	0.2851	0.0572	-0.0241	0.1271	0.0773	-0.1683
0.7916	1.6497	0.2099	1.1276	-0.3790	-0.5238	1.0195	0.2982	0.6713	0.4742
0.7904	-1.6227	-0.9065	1.1719	-0.3811	-0.2852	0.0321	-0.1050	-0.2122	-0.0199
0.8946	1.1556	-1.2946	-1.6637	0.4986	-0.0789	-0.1761	-0.1087	0.1217	-0.0507
0.6513	0.5604	0.0766	0.6119	0.3411	0.3541	-0.8634	-0.4928	-1.1168	-0.8213
0.1017	-0.0749	-0.0575	0.0129	-0.0320	-0.2591	0.0384	0.1043	0.0009	0.0120
-0.8417	0.6470	-1.0559	0.8239	1.0290	-0.6766	-0.3045	0.0840	0.1413	-0.0101
1.0577	-0.3583	1.1956	-0.6993	-0.9028	0.9387	0.3171	-0.1756	-0.0675	0.1132

0.1591	-0.4417	0.5265	-0.6670	-0.1858	-0.1850	0.1112	-0.0249	0.0124	-0.0224
0.3424	0.7840	1.2064	1.0877	0.6904	0.8719	-0.3541	0.0182	0.2859	0.0674
0.2891	0.4322	0.6162	-0.1750	-0.8576	-1.9468	-0.2864	-0.3193	-0.3708	-0.1428
0.7183	0.3454	-0.6067	0.0246	0.5469	0.8487	0.2574	0.3375	-0.0305	0.0585
0.1084	-1.3909	-0.4958	-0.2760	0.2501	-0.0845	0.0718	-0.1358	1.3571	-0.9164
-0.1437	-1.0939	-0.3012	-0.3351	0.2941	-0.0913	-0.9474	0.5980	-0.1889	1.3210
-0.9956	0.3027	-1.4726	-0.1825	-1.1229	0.5953	1.0285	-0.3990	-0.5614	0.1007

Latent =

1.0e+006 *

3.4204
3.1118
3.0979
2.9129
1.9901
1.6222
1.3669
1.0984
0.9962
0.7494
0.7303
0.6967
0.6775
0.5550
0.4524
0.4091
0.3397
0.2866
0.2481
0.2024

5.2 LIMITATIONS OF THE PROPOSED ALGORITHM:

Specifically the important issues involved are

- Non-frontal view of the face (3D pose, head movement)
- Invariance to lighting conditions.
- Facial occlusion (sunglasses, hat, scarf, etc).
- Invariance to aging.

Chapter 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION:

In this project the particular method using Principal Component Analysis for facial expression detection was initially started with 3 training images and 6 testing images from each class of expression. After that the same procedure was repeated by increasing the number of training images from each class of expression and decreasing the number of testing images. The principal components are selected for each class independently to reduce the eigenspace. With these eigenvectors the input test images were classified based on Euclidian distance. The proposed method was tested on database of 30 different persons with different expressions. The proposed PCA method has the greater accuracy with consistency. The recognition rate was greater even with the small number of training images which demonstrated that it is fast, relatively simple, and works well in a constrained environment.

6.2 FUTURE SCOPE:

This project is based on eigenface approach that gives an accuracy maximum Percentage. Adaptive algorithms may be used to obtain an optimum threshold value. There is a scope for future betterment of the algorithm by using Neural Network technique that can give better results as compared to eigenface approach. With the help of neural network technique accuracy can be improved.

The whole software is dependent on the database and the database is dependent on resolution of camera. So if good resolution digital camera or good resolution analog camera is used , the results could be considerably improved.

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